



**Optimization of Sampling Times for PK/PD Models:
Approximation of Elemental Fisher Information Matrix**

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Comparison of software tools

PODE 2007, 2009 meetings:

- PFIM (developed in INSERM, Université Paris 7, France);
- PkStaMp (GlaxoSmithKline, Collegeville, U.S.A.);
- PopDes (CAPKR, University of Manchester, UK);
- PopED (Uppsala University, Sweden) and
- WinPOPT (University of Otago, New Zealand).

Key for model-based optimal designs: Fisher information matrix of a properly defined single observational unit

This presentation:

- Some results of comparison at PODE 2009
- Certain options of calculating/approximating FIM

PODE 2009 comparison

Goal: compare results (information matrix) for a particular model and particular sequence of sampling times

Model: one-compartment, 1st order absorption, single dose $D = 70$ mg at $t = 0$

$$f(x, \gamma) = \frac{Dk_a}{V(k_a - k_e)} (e^{-k_e x} - e^{-k_a x}). \quad (1)$$

Response parameters $\gamma = (k_a, CL, V)$, $k_e = CL/V$

Individual parameters

$$\gamma_i = \gamma^0 e^{\eta_i}, \quad \eta_i \sim \mathcal{N}(\mathbf{0}, \mathbf{\Omega}), \quad (2)$$

$$\gamma^0 = (1, 0.15, 8), \quad \mathbf{\Omega} = \text{diag}(0.6, 0.07, 0.02)$$

PODE 2009 comparison (cont.)

Measurements:

$$y_{ij} = f(\gamma_i, x_{ij}) [1 + \varepsilon_{M,ij}] + \varepsilon_{A,ij}, \quad (3)$$

$\{x_{ij}\} \equiv \mathbf{x} = (0.5, 1, 2, 6, 24, 36, 72, 120)$ hours

$$\begin{aligned} \varepsilon_{A,ij} &\sim \mathcal{N}(0, \sigma_A^2), \quad \varepsilon_{M,ij} \sim \mathcal{N}(0, \sigma_M^2), \\ \sigma_A^2 &= 0, \quad \sigma_M^2 = 0.01; \quad i = 1, \dots, 32; \quad j = 1, \dots, 8 \end{aligned}$$

Combined parameter

$$\boldsymbol{\theta} = (k_a^0, CL^0, V^0; \omega_{k_a}^2, \omega_{CL}^2, \omega_V^2; \sigma_M^2)$$

Individual information matrix $\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta})$

$\mathbf{x} = (x_1, x_2, \dots, x_k)$ - sequence of sampling times

$\mathbf{Y} = [y(x_1), \dots, y(x_k)]^T$ - observations

$\mathbf{f} = \mathbf{f}(\mathbf{x}, \boldsymbol{\theta}) = \mathbf{E}_{\boldsymbol{\theta}}(\mathbf{Y}) = [f(x_1, \boldsymbol{\theta}), \dots, f(x_k, \boldsymbol{\theta})]^T$ (mean)

$\mathbf{S} = \mathbf{S}(\mathbf{x}, \boldsymbol{\theta}) = \mathbf{Var}_{\boldsymbol{\theta}}(\mathbf{Y})$ (variance)

Key formula for Gaussian observations $\mathbf{Y} \sim \mathcal{N}(\mathbf{f}, \mathbf{S})$:

$$\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta}) = [\mu_{\alpha\beta}(\mathbf{x}, \boldsymbol{\theta})]_{\alpha,\beta=1}^m, \quad \text{Magnus and Neudecker (1988)}$$

$$\mu_{\alpha\beta}(\mathbf{x}, \boldsymbol{\theta}) = \frac{\partial \mathbf{f}}{\partial \theta_{\alpha}} \mathbf{S}^{-1} \frac{\partial \mathbf{f}}{\partial \theta_{\beta}} + \frac{1}{2} \text{tr} \left[\mathbf{S}^{-1} \frac{\partial \mathbf{S}}{\partial \theta_{\alpha}} \mathbf{S}^{-1} \frac{\partial \mathbf{S}}{\partial \theta_{\beta}} \right]. \quad (4)$$

Individual information matrix $\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta})$ (cont.)

Once $\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta})$ is calculated (approximated) for any candidate sequence \mathbf{x} , the numerical construction of locally optimal designs is easy!

- Define normalized matrix $\mathbf{M}(\xi, \boldsymbol{\theta})$, w/o or with costs,

$$\mathbf{M}(\xi, \boldsymbol{\theta}) = \sum_i p_i \boldsymbol{\mu}(\mathbf{x}_i, \boldsymbol{\theta}), \quad p_i \in [0, 1], \quad \xi = \{p_i, \mathbf{x}_i\}$$

- Specify a criterion of optimality Ψ (D-, A-, c- etc.)
- Solve optimization problem $\Psi [\mathbf{M}^{-1}(\xi, \boldsymbol{\theta})] \rightarrow \min_{\xi}$
(1st order optimization algorithm in the space of information matrices $\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta})$, $\mathbf{x} \in \mathbf{X}$ - design region)

Information matrix $\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta})$ (cont.)

- Formula (4) is exact for normal Y only
- Need expressions (approximations?) of \mathbf{f} and \mathbf{S}
- First-order approximation (Taylor series):

$$\mathbf{E}_{\boldsymbol{\theta}}(\mathbf{Y}) = [f(x_1, \boldsymbol{\gamma}^0), \dots, f(x_k, \boldsymbol{\gamma}^0)]^T = \mathbf{f}(\mathbf{x}, \boldsymbol{\gamma}^0) \quad (5)$$

$$\begin{aligned} \mathbf{Var}_{\boldsymbol{\theta}}(\mathbf{Y}) = \mathbf{S}(\mathbf{x}, \boldsymbol{\theta}) = & \mathbf{F} \boldsymbol{\Omega} \mathbf{F}^T + \sigma_A^2 \mathbf{I}_k + \\ & + \sigma_M^2 \text{Diag} [\mathbf{f}(\mathbf{x}, \boldsymbol{\gamma}^0) \mathbf{f}^T(\mathbf{x}, \boldsymbol{\gamma}^0) + \mathbf{F} \boldsymbol{\Omega} \mathbf{F}^T], \quad (6) \end{aligned}$$

$$\mathbf{F} = \left[\frac{\partial \mathbf{f}(\mathbf{x}, \boldsymbol{\gamma}^0)}{\partial \gamma_\alpha} \right] \text{ -- } (k \times m_1)\text{-matrix, } m_1 = \dim(\boldsymbol{\gamma}) = 3$$

Gagnon and Leonov (2005)

Information matrix $\mu(\mathbf{x}, \boldsymbol{\theta})$ (cont.)

First round of PODE 2009 comparison, expression for FIM:
very similar results for coeff. of variation (CV) except k_a

(i) PFIM, PopED, WinPOPT: $CV(k_a) \simeq 13.9\%$

(ii) PkStaMp, PopDes: $CV(k_a) \simeq 4.8\%$, why such discrepancy??

(iii) Simulations in NONMEM/MONOLIX: $CV(k_a) \simeq 12 - 13\%$,
why closer to (a)??

Information matrix $\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\theta})$ (cont.)

Matrix $\boldsymbol{\mu}$ in (4): block form, *Retout and Mentré (2003)*

$$\boldsymbol{\mu} = \begin{Bmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{C}^T & \mathbf{B} \end{Bmatrix}, \quad (7)$$

$$\begin{aligned} \mathbf{A} &= \mathbf{F}^T \mathbf{S}^{-1} \mathbf{F} + \frac{1}{2} \text{tr} \quad (\text{derivatives wrt } \gamma_\alpha) \\ \mathbf{C} &= \frac{1}{2} \text{tr} \quad (\text{mixed derivatives wrt } \gamma_\alpha \text{ and } [\omega_\beta^2, \sigma_M^2]) \\ \mathbf{B} &= \frac{1}{2} \text{tr} \quad (\text{derivatives wrt } [\omega_\beta^2, \sigma_M^2]) \end{aligned}$$

PkStaMp in (i): used (5), (6) and FULL matrix $\boldsymbol{\mu}$ in (7)

If (1) Block \mathbf{C} “excluded” ($\mathbf{C} = \mathbf{0}$)

(2) Second term in \mathbf{A} (trace) removed

(3) No term $\mathbf{F} \boldsymbol{\Omega} \mathbf{F}^T$ in square brackets in (6) \implies
then exact match with (ii)

Which approximation to choose?

Types of approximation

A1. Log-normal distribution in (2)

- *1st-order approximation*, $\mathbf{E}\eta_i = 0$, $\mathbf{Var}(\eta_i) = V \implies$

$$\mathbf{E}_\eta(\theta e^{\eta_i}) \simeq \theta, \quad \mathbf{Var}_\eta(\theta e^{\eta_i}) \simeq \theta^2 V$$

- *Exact moments*:

$$\mathbf{E}_\eta(\theta e^{\eta_i}) = \theta e^{V/2}, \quad \mathbf{Var}_\eta(\theta e^{\eta_i}) = \theta^2 e^V (e^V - 1).$$

- If $\theta = 1$, $V = 0.6$ (as for k_a), then

$$\mathbf{E}_{1st} = 1, \quad \mathbf{E}_{exact} = 1.35; \quad \mathbf{Var}_{1st} = 0.6, \quad \mathbf{Var}_{exact} = 1.50$$

Types of approximation (cont.)

A2. Trace (2nd) term in (4): let

- $k = 1$ (single response) and

- $\mathbf{Var}(y) = S = \sigma^2 f^2$ with known σ^2 ; cf. (3)

↓

$$\boldsymbol{\mu} = \frac{1}{\sigma^2} \frac{\mathbf{F}^T \mathbf{F}}{f^2} + 2 \frac{\mathbf{F}^T \mathbf{F}}{f^2} = \left(\frac{1}{\sigma^2} + 2 \right) \frac{\mathbf{F}^T \mathbf{F}}{f^2} \quad (8)$$

To examine the effect of missing 2nd term on CV, check

$$\sqrt{\frac{\mu_{\alpha\beta, FULL}}{\mu_{\alpha\beta, 1st\ term}}} = \sqrt{\frac{2 + 1/\sigma^2}{1/\sigma^2}} = \sqrt{1 + 2\sigma^2} \sim 1 + \sigma^2 \implies$$

Inflation coefficient for CV: $1 + \sigma^2$, $\sigma^2 \leq 0.25$

Types of approximation (cont.)

A3. Second-order approximation for mean/variance:

Fedorov, Leonov (2005)

$$\mathbf{E}_{\boldsymbol{\theta}}[f(x, \gamma_i)] \approx f(x, \boldsymbol{\gamma}^0) + \frac{1}{2} \text{tr} [\mathbf{H}(\boldsymbol{\gamma}^0)\boldsymbol{\Omega}] , \quad (9)$$

$$\mathbf{H}(\boldsymbol{\gamma}^0) = \left[\frac{\partial^2 f(x, \boldsymbol{\gamma})}{\partial \gamma_\alpha \partial \gamma_\beta} \right] \Big|_{\boldsymbol{\gamma}=\boldsymbol{\gamma}^0} \text{ etc} \implies$$

numerically may be rather tedious

Types of approximation (cont.)

A4. Calculation of mean/variance via Monte Carlo:

$$\hat{f}(x_j) = \widehat{\mathbf{E}}_{\boldsymbol{\theta}}(y_{ij}) = \frac{1}{N} \sum_{i=1}^N y_{ij} , \quad (10)$$

$$\hat{S}(x_j) = \widehat{\mathbf{Var}}_{\boldsymbol{\theta}}(y_{ij}) = \frac{1}{N} \sum_{i=1}^N [y_{ij} - \hat{f}(x_j)]^2 \implies$$

Numerically straightforward: valid option if normal approximation is “reasonable” (??)

Comparison of approximation options

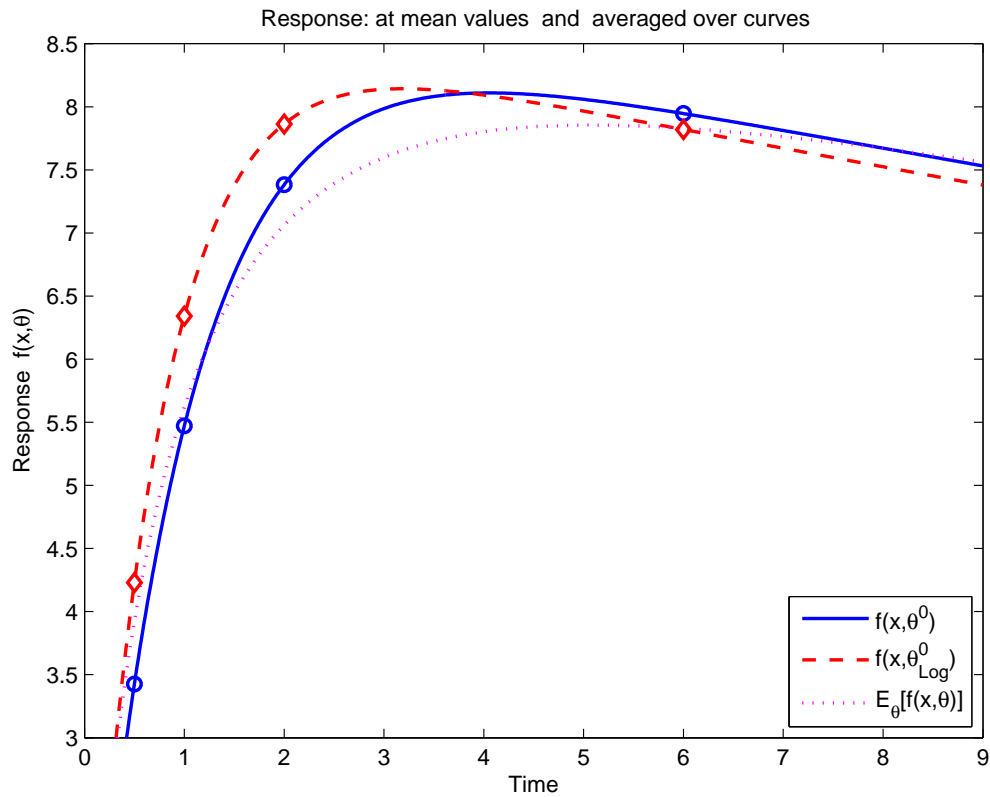


Figure 1: Mean response curves for PODE 2009 example. Solid - 1st order approximation, dashed - computed at mean values of log-normal distribution, dotted - Monte Carlo average as in (10)

For a single response parameter, $m = 1$:

$$\mathbf{E}_{\theta}[f(x, \theta_i)] \approx f(x, \theta^0) + \frac{1}{2} f''(x, \theta) \mathbf{Var}(\theta)$$

Comparison of approximation options (cont.)

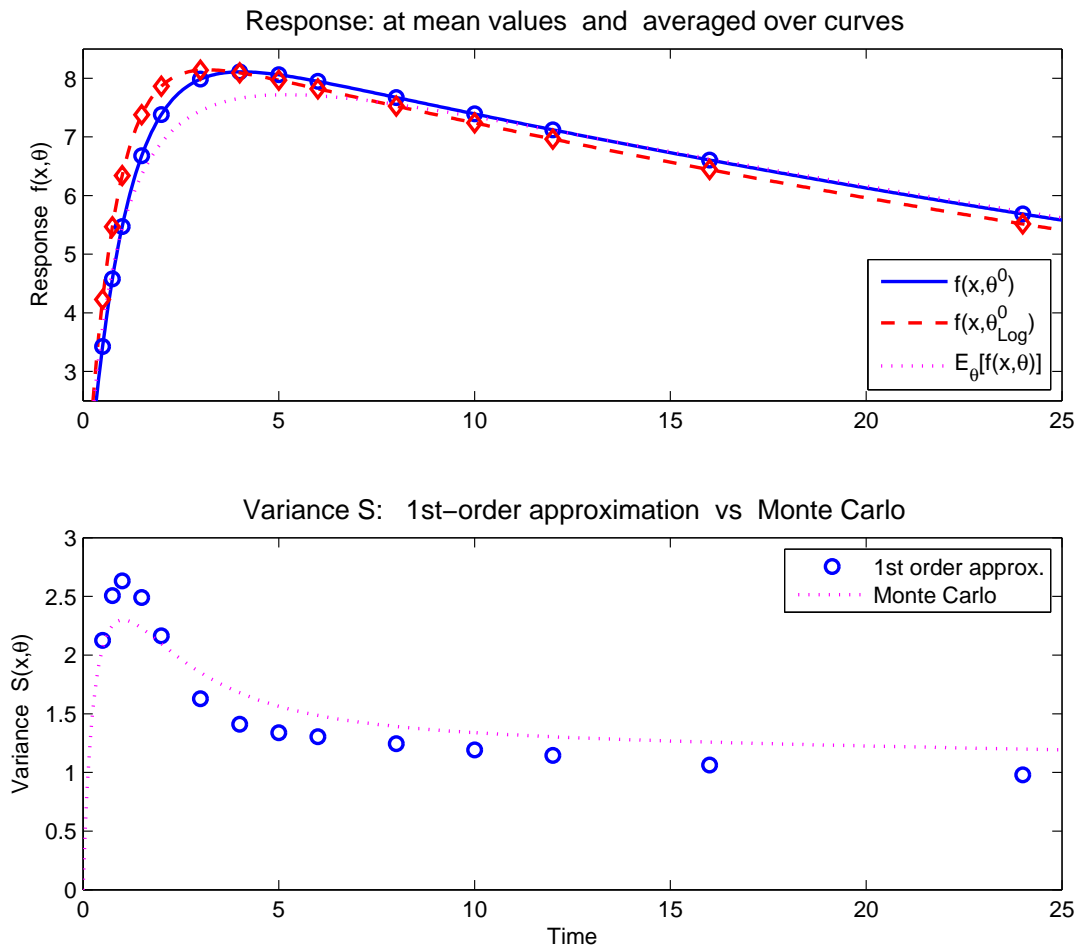


Figure 2: Mean response curves and variance. Legend similar to Fig. 1

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